Analysis of cross-sectional neural network recognition of satellite and aerial survey data

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Abstract

Modern advances in the field of neural network data recognition open new perspectives for the use of satellite and aerial photography in aerospace research. The use of unmanned aerial vehicles (UAVs) is becoming increasingly important in various fields, including military, environmental, and agro-industrial applications. However, the issue of automating the processing and analysis of data obtained from satellite and aerial surveys remains relevant in terms of the implementation of these technologies. In this study, we focus on the analysis of the effectiveness of cross-sectional neural network recognition, which was performed on both satellite and aerial (UAV). One of the key problems is the need to implement automated methods of analysis and classification of images obtained from different sources. In the context of using satellite data in aerospace applications, it is important to understand how effectively neural networks can adapt to changes in information sources.

Keywords

neural network, data, recognition, image, dataset, satellite, aerial survey

1. Preparation

It is important to note that both areas of data acquisition are extremely fruitful in their own right. For example, every single set presented in this paper has already been used for research. So, with the help of satellite data sets, various types of convolutions were studied by neural network classifiers and their applications [1–4]. The " Aerial Survey " dataset and its separate parts have been the basis for scientific works of various levels for several years [5–10]. A comparative element is also quite common, for example, a large part of the work [6] contains a description of the advantages of one type of data over another.

Recent scientific studies, such as work [7], have already emphasized the importance of cross-training to achieve high accuracy when working with heterogeneous data. Our approach complements these studies by focusing on the specific challenges and opportunities associated with adapting neural networks to satellite and aerial imagery processing.

The purpose of this research is to determine the possibilities of using satellite and aerial photography in interaction with unmanned aerial vehicles. Investigating how neural networks of the same architecture and other hyperparameters, trained on different types of data, can adapt and effectively recognize objects and phenomena on the ground, we set ourselves the task of improving systems for automatic analysis of information received in real-time. For neural network recognition, was selected a part of the " Aerial Survey " dataset [5], which was formed from data obtained from UAVs, as well as four datasets consisting of satellite images [1–4]. The structure of each set and conventions for convenient abbreviation are presented in Tables 1 – 5.

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It should be noted that the primary goal of the study was to check the possibility of expanding the dataset of aerial photography. That is why the present sets were studied in this ratio (4 satellite to 1 aerial survey).

Table 1
Structure of the "Aerial survey" Set

Class name	Description	The number of digital images	Mark
Factory	Industrial building	360	B.1.1
Forest	Forests, spring-summer period (without snow)	2132	B.1.2
Vehicles	Road transport	5921	B.1.3
Non vegetation field	Soil fields (without vegetation)	2175	B.1.4
Not factory	Not an industrial building	1979	B.1.5
Pillars	Pillars (separate, roadside)	1188	B.1.6
Residential	A cluster of residential buildings	386	B.1.7
Roads	The roads	4236	B.1.8
Vegetation_field	Fields with vegetation	1875	B.1.9
Water	Reservoirs with coastline	879	B.1.10

Table 2
Structure of the "EuroSAT" Set

Class name	Description	The number of digital images	Mark
Annual Crop	Agricultural fields with annual crops	3000	P.1.1
Forest	Forest landscape, without snow	3000	P.1.2
Herbaceous Vegetation	Fields with grass vegetation	3000	P.1.3
Highway	Roads, tracks	2500	P.1.4
Industrial	Industrial building	2500	P.1.5
Pasture	Pastures	2000	P.1.6
Permanent Crop	Agricultural fields with perennial crops	2500	P.1.7
Residential	A cluster of residential buildings	3000	P.1.8
River	Rivers	2500	P.1.9
Sea Lake	Reservoirs, sea canvas	3000	P.1.10

Table 3
Structure of the "AID" Set

Class name	Description	The number of digital images	Mark
Airport	Areas designated for aviation services, including runways and airport infrastructure	360	C.2.1
BareLand	Areas with no significant vegetation or cover, such as bare ground or areas without vegetation	310	C.2.2
BaseballField	Baseball pitches with a distinctive configuration	220	C.2.3
Beach	Places where the shore and the water meet, with a sandy or rocky surface	400	C.2.4
Bridge	Structures for crossing water obstacles or other areas, usually with a building structure	360	C.2.5
Center	Central parts of cities or settlements with intensive construction and infrastructure	260	C.2.6
Church	Religious buildings, such as churches or temples	240	C.2.7
Commercial	Areas designated for commercial activities, such as business centers, shops and offices	350	C.2.8
Industrial	Territories with industrial infrastructure	390	C.2.9
Meadow	Open spaces with natural grass vegetation	280	C.2.10
Medium Residential	Areas with a moderate density of residential development and residential buildings	290	C.2.11
Mountain	Mountain regions with a characteristic landscape	340	C.2.12
Park	Territories intended for recreation	350	C.2.13
Parking	Areas for parking vehicles	390	C.2.14
Playground	Areas with children's playgrounds	370	C.2.15
Pond	The reservoir is smaller in size and shallow	420	C.2.16
Port	Areas of port infrastructures for sea transport	380	C.2.17
Railway Station	Territories of railway hubs and infrastructure	260	C.2.18
Resort	Recreation areas	290	C.2.19
River	Large water streams	410	C.2.20
School	Territories of educational institutions	300	C.2.21
Sparse Residential	Areas with a low density of residential buildings	300	C.2.22
Square	Large open areas or squares in cities	330	C.2.23
Stadium	Areas with sports grounds for games and events	290	C.2.24
StorageTanks	Areas with tanks for storing various substances	360	C.2.25
Viaduct	Bridge-like structures that cross various obstacles	420	C.2.26
DenseResidential	Areas with a high density of residential buildings	410	C.2.27
Desert	Dry areas with a characteristic landscape	300	C.2.28
Farmland	Territories for agricultural production with crops	370	C.2.29
Forest	Areas with dense forest vegetation	250	C.2.30

Table 4
Structure of the Set "NWPU-RESISC45"

Class name	Description	The number of digital images	Mark
airplane	Areas with images of aircraft in various operating conditions	700	C.3.1
airport	Areas of airports with runways and infrastructure for aviation services	700	C.3.2
baseball_diamond	Images of baseball fields and their infrastructure	700	C.3.3
basketball_court	Photos of basketball courts and their surroundings	700	C.3.4
beach	Coasts and coastal areas with sandy or rocky surfaces	700	C.3.5
bridge	Structures for crossing water obstacles or other areas, usually with a building structure	700	C.3.6
chaparral	Image of areas with characteristic vegetation	700	C.3.7
church	Religious buildings, such as churches or temples	700	C.3.8
circular_farmland	Areas with circular or elliptical agricultural fields	700	C.3.9
cloud	Areas with images of clouds or cloud formations	700	C.3.10
commercial_area	Areas designated for commercial activities, such as business centers, shops and offices	700	C.3.11
dense_residential	Areas with a high density of residential buildings	700	C.3.12
desert	Dry, sparsely populated areas with a characteristic landscape	700	C.3.13
forest	Areas with dense forest vegetation	700	C.3.14
freeway	Territories with a highway and road infrastructure facilities	700	C.3.15
golf_course	Images of golf courses and their infrastructure.	700	C.3.16
ground_track_field	Photos of sports grounds for running and other sports	700	C.3.17
harbor	Areas with port infrastructure for receiving and servicing ships	700	C.3.18
industrial_area	Territories with industrial infrastructure, factories and other industrial facilities	700	C.3.19
intersection	Road intersection areas with road infrastructure	700	C.3.20
island	Areas with the image of islands surrounded by water bodies	700	C.3.21
lake	Areas with large bodies of water, such as lakes	700	C.3.22
meadow	Open spaces with natural grass vegetation	700	C.3.23
medium_residential	Areas with a moderate density of residential development and residential buildings	700	C.3.24
mobile_home_park	Territories with stationary or mobile homes	700	C.3.25

mountain	High mountain regions with a characteristic landscape	700	C.3.26
overpass	Structures that cross and pass over other roads or objects	700	C.3.27
palace	Areas with images of palaces or historical buildings	700	C.3.28
parking_lot	Photos of areas for parking vehicles	700	C.3.29
railway	Territories with railway infrastructure and roads	700	C.3.30
railway_station	Areas of railway hubs and infrastructure	700	C.3.31
rectangular_farmland	Areas with rectangular or square agricultural fields	700	C.3.32
river	Large water streams	700	C.3.33
roundabout	Areas with roundabouts	700	C.3.34
runway	Photos of airport runways	700	C.3.35
sea_ice	Areas with ice cover on seas and oceans	700	C.3.36
ship	Areas with the image of large water vessels	700	C.3.37
snowberg	Territories with the image of large mountain snow landscapes	700	C.3.38
sparse_residential	Areas with a low density of residential buildings	700	C.3.39
stadium	Territories with large sports grounds for holding games and events	700	C.3.40
tennis_court	Photos of tennis courts and their surroundings	700	C.3.41
terrace	Territories with a terraced relief structure	700	C.3.42
thermal_power_station	Territories with thermal power plants and energy infrastructure	700	C.3.43
wetland	Areas depicting wetlands and swamps	700	C.3.44
storage_tank	Areas with tanks for storing various substances	700	C.3.45

A neural network was used to conduct the research coagulation classifier (a classifier based on a convolutional artificial neural network, created with [11]), the structure of which is illustrated in Figure 1. We also note that all images undergo reprocessing, during which their size is also unified, which at the beginning of processing is 64 by 64 pixels.

During the experiment, each of the satellite datasets was pairwise compared with the UAV set. The essence of the comparison was that in each pair of singulars, the data set first served as a training one, and the second as a test one. Thus, we were able to observe how the data from the test set will be reflected on the data from the set for training the network (training).

After receiving the result, the datasets in pairs changed roles and the learning and testing process began anew. Thus, we were able to evaluate which classes from the satellite sets are better displayed (recognized) in the classes from the UAV set and vice versa.

For convenience, these data are presented in the form of matrices with a color scale (Table 6), in which you can see which frequency of a particular class was reflected on the classes from the training set.

Table 5
Structure of the Set "UCMerced _ LandUse"

Class name	Description	The number of digital images	Mark
agricultural	Areas used for agricultural activities, such as fields where different crops are grown	100	C.4.1
airplane	Images of aerial vehicles	100	C.4.2
baseballdiamond	Image of baseball fields with a characteristic configuration	100	C.4.3
beach	Places where the shore meets the water, with a sandy or rocky surface	100	C.4.4
buildings	Areas with a concentration of buildings, including residential, commercial and other structures	100	C.4.5
chaparral	Regions with dense shrub vegetation	100	C.4.6
dense residential	Areas with a high density of residential buildings	100	C.4.7
forest	Territories with dense forest vegetation	100	C.4.8
freeway	Motorways and expressways for automobile traffic	100	C.4.9
golfcourse	Golf courses	100	C.4.10
harbor	Areas of port infrastructure for parking and maintenance of ships	100	C.4.11
intersection	Images of road intersections and crossed roads	100	C.4.12
mediumresidential	Areas with a moderate density of residential buildings	100	C.4.13
mobilehomepark	Areas with parks for mobile homes and residential facilities	100	C.4.14
overpass	Above-ground structures for crossing other roads or obstacles	100	C.4.15
parkinglot	Territories for parking vehicles	100	C.4.16
river	Large water streams	100	C.4.17
runway	Runways for aircraft	100	C.4.18
sparseresidential	Areas with a low density of residential buildings	100	C.4.19
storagetanks	Areas with tanks for storing various substances	100	C.4.20
tenniscourt	Tennis courts	100	C.4.21

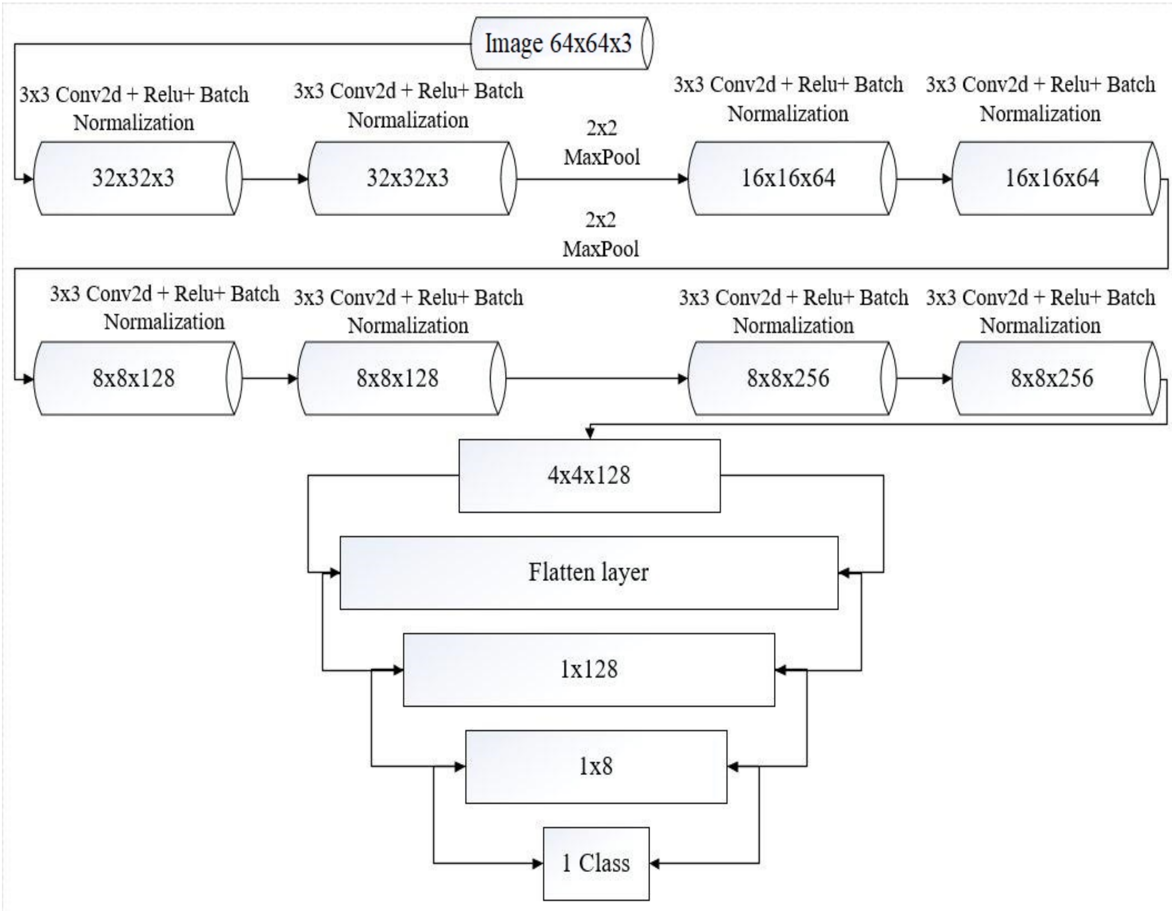


Figure 1: Architecture of the used classifier.

Table 6
Display Level Scale

Scale
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10

2. Experiment results

Tables 7–14 present the results of a pairwise mapping study. Since some satellite datasets contain a significant number of classes, all tables are reduced to a view where satellite classes are arranged horizontally (rows) and UAV classes vertically (columns).

In this case, you can understand which classes were included in the educational sample (the one in which it is displayed) from the name of the table. For example, in Table 8 it is B.1, vertical, and in Table 7 it is C.1, horizontal.

Table 7
The Result of Mapping Aerial Photographs from (B.1) into Classes from (C.1)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
P.1.1	0	0.33	0.07	0.19	0	0.10	0	0.08	0.05	0.02
P.1.2	0	0.01	0	0.03	0	0	0	0	0.30	0.20
P.1.3	0.26	0.55	0.40	0.42	0.17	0.38	0	0.38	0.13	0.23
P.1.4	0	0	0.02	0	0.03	0.03	0	0.20	0	0.01
P.1.5	0.57	0	0.13	0	0.71	0.01	0.01	0.07	0.05	0.03
P.1.6	0	0	0	0.02	0	0.02	0	0	0	0
P.1.7	0	0.01	0	0.24	0.03	0	0	0.02	0	0.02
P.1.8	0.16	0.08	0	0.01	0.05	0.02	0.97	0	0	0.04
P.1.9	0	0	0.14	0	0.01	0.05	0.01	0.14	0	0.19
P.1.10	0.01	0	0.23	0.09	0	0.39	0.01	0.11	0.47	0.43

Table 8
The Result of Mapping Satellite Images from (C.1) into Classes from (B.1)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
P.1.1	0	0.01	0.02	0.05	0.17	0.04	0	0.13	0.01	0.57
P.1 .2	0	0.06	0	0.01	0	0.11	0	0	0.03	0.79
P.1.3	0.09	0.07	0.01	0.45	0.05	0.17	0.01	0.04	0.01	0.11
P.1.4	0.02	0.01	0.04	0.02	0.09	0.38	0.03	0.27	0	0.14
P.1.5	0.05	0	0.43	0	0.39	0.01	0.10	0.02	0	0
P.1.6	0	0.06	0.01	0.02	0	0.35	0	0	0.02	0.53
P.1.7	0.05	0.07	0.02	0.25	0.15	0.16	0.02	0.07	0.01	0.20
P.1.8	0.09	0.05	0.02	0.11	0.08	0.01	0.63	0	0	0.01
P.1.9	0	0.01	0.03	0	0.01	0.16	0.01	0.03	0.01	0.73
P.1.10	0	0	0	0	0	0.08	0	0	0.02	0.90

Table 9
The Result of Mapping Aerial Photographs from (B.1) into Classes from (S.2)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.2.1	0.24	0	0.05	0	0.19	0.02	0	0.14	0	0.02
C.2.2	0.03	0.01	0.05	0.35	0	0.12	0	0.11	0.01	0.21
C.2.3	0	0	0.01	0	0	0	0	0	0	0
C.2.4	0.04	0	0.07	0.01	0.02	0.08	0.52	0.15	0.11	0.16
C.2.5	0.10	0	0.02	0.01	0.02	0.11	0	0.19	0	0.21
C.2.6	0.20	0	0.07	0	0.13	0.01	0	0	0	0.01
C.2.7	0.03	0	0	0	0.06	0	0	0	0	0
C.2.8	0	0	0	0	0.01	0	0	0	0	0
C.2.9	0.03	0	0	0	0.07	0	0	0	0	0.07
C.2.10	0	0	0	0.03	0	0.04	0	0.01	0.77	0
C.2.11	0	0	0.02	0	0.01	0.02	0.01	0	0	0.01
C.2.12	0	0.17	0	0	0.03	0	0	0.02	0	0.01
C.2.13	0	0.02	0	0	0	0	0	0	0	0
C.2.14	0.04	0	0	0	0.04	0	0	0	0	0
C.2.15	0	0	0.02	0	0.04	0.01	0	0.02	0.01	0
C.2.16	0	0	0.02	0	0.01	0	0	0	0	0.06
C.2.17	0.02	0	0	0	0.01	0	0.01	0	0	0.04
C.2.18	0.01	0	0	0.01	0.01	0	0	0.03	0	0.01
C.2.19	0	0.01	0.01	0	0.02	0	0.01	0.01	0	0.03
C.2.20	0.01	0.01	0.05	0	0.01	0.01	0	0.07	0	0.04
C.2.21	0.01	0.04	0	0	0.11	0	0.27	0	0	0
C.2.22	0	0	0.07	0	0	0	0	0	0	0
C.2.23	0.08	0.17	0.14	0	0.14	0.07	0	0.07	0	0.02

C.2.24	0.01	0	0.01	0	0.02	0	0	0	0	0
C.2.25	0.01	0	0.20	0	0.01	0	0	0	0	0
C.2.26	0.03	0	0	0	0.02	0	0	0.02	0	0
C.2.27	0	0.20	0	0.13	0.01	0	0.02	0	0	0
C.2.28	0	0	0.15	0.17	0	0.37	0	0.04	0.01	0
C.2.29	0.10	0.38	0.02	0.28	0.01	0.12	0	0.09	0.07	0.05
C.2.30	0	0.15	0	0.01	0	0	0.15	0	0.01	0.04

Table 10

The Result of Mapping Satellite Images from (S.2) into Classes from (B.1)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.2.1	0.16	0.01	0.04	0	0.59	0.01	0.01	0.12	0	0.06
C.2.2	0.02	0.14	0.09	0.32	0.10	0.08	0	0.14	0.04	0.07
C.2.3	0.09	0.02	0.05	0	0.35	0.03	0	0.22	0	0.25
C.2.4	0.10	0.01	0.12	0	0.16	0.02	0.03	0.14	0.09	0.33
C.2.5	0.25	0.01	0.02	0	0.12	0.15	0.01	0.16	0	0.28
C.2.6	0.19	0	0.03	0	0.78	0	0	0	0	0
C.2.7	0.30	0.04	0.01	0	0.63	0	0	0	0	0.02
C.2.8	0.07	0.08	0	0	0.73	0	0.11	0	0	0.01
C.2.9	0.05	0.01	0.05	0	0.83	0	0.03	0.01	0.01	0.01
C.2.10	0	0.06	0.26	0.28	0	0.01	0	0.04	0.34	0
C.2.11	0.18	0.27	0.02	0.02	0.30	0	0.18	0.02	0	0.02
C.2.12	0.04	0.27	0.25	0.03	0.17	0.02	0.01	0.08	0.01	0.12
C.2.13	0.18	0.16	0.07	0.01	0.20	0.03	0.22	0.03	0.01	0.10
C.2.14	0.06	0.02	0.02	0	0.85	0.01	0.03	0	0.01	0.01
C.2.15	0.15	0.02	0.02	0	0.36	0.01	0.01	0.18	0.01	0.24
C.2.16	0.08	0.01	0	0	0.08	0.02	0	0.02	0	0.79
C.2.17	0.26	0	0.03	0	0.33	0.05	0.14	0	0	0.19
C.2.18	0.10	0.05	0.07	0.01	0.37	0.03	0.22	0.11	0	0.03
C.2.19	0.07	0.04	0.05	0.01	0.70	0.01	0.06	0.03	0	0.03
C.2.20	0.03	0.18	0.09	0.01	0.06	0.11	0.02	0.18	0	0.30
C.2.21	0.22	0.05	0.04	0	0.59	0.01	0.05	0.02	0	0.01
C.2.22	0.09	0.35	0.31	0	0.03	0.09	0.01	0	0	0.10
C.2.23	0.12	0.07	0.03	0	0.70	0.01	0.01	0.03	0	0.04
C.2.24	0.24	0	0.01	0	0.72	0	0	0.01	0	0.01
C.2.25	0.03	0.01	0.25	0.01	0.69	0	0	0.01	0	0.01
C.2.26	0.23	0.08	0.03	0	0.31	0.03	0.03	0.22	0	0.07
C.2.27	0.03	0.22	0.10	0.06	0.44	0	0.10	0	0.05	0
C.2.28	0	0.03	0.38	0.47	0.02	0.01	0	0.06	0.02	0.01
C.2.29	0.02	0.26	0.05	0.08	0.07	0.20	0.04	0.10	0.03	0.16
C.2.30	0	0.68	0.21	0	0	0	0.04	0.01	0.02	0.03

Table 11

The result of Mapping Aerial Photographs from (B.1) into Classes from (S.3)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.3.1	0.19	0	0.05	0.08	0.05	0.15	0	0.07	0	0.02
C.3.2	0.03	0	0	0	0.02	0.01	0	0.01	0	0
C.3.3	0	0	0	0	0	0	0	0	0	0
C.3.4	0.07	0	0	0.04	0.09	0	0	0.01	0	0
C.3.5	0	0	0.01	0	0.01	0.04	0	0.06	0.02	0.16
C.3.6	0.03	0	0	0.01	0	0.09	0	0.04	0.08	0.05
C.3.7	0	0	0	0	0	0	0	0	0	0
C.3.8	0.02	0	0.03	0	0.10	0	0	0	0	0
C.3.9	0	0.01	0	0	0	0	0	0	0	0
C.3.10	0.03	0.22	0.49	0	0.11	0.14	0	0.08	0	0.02

C.3.11	0.01	0.04	0	0	0.02	0	0	0	0	0
C.3.12	0	0.01	0	0	0.03	0	0.01	0	0	0
C.3.13	0	0.01	0.02	0.20	0	0.03	0	0.03	0.03	0.01
C.3.14	0	0.09	0	0	0	0	0	0	0	0
C.3.15	0.01	0	0	0.01	0.01	0	0.01	0.06	0	0.01
C.3.16	0	0	0	0	0	0	0	0	0	0
C.3.17	0	0	0	0	0	0	0	0	0	0
C.3.18	0	0	0	0	0	0	0.13	0	0	0
C.3.19	0.02	0.01	0	0	0.08	0	0.01	0	0	0
C.3.20	0	0	0	0	0.01	0	0	0	0	0
C.3.21	0	0	0.09	0.02	0	0.15	0	0.03	0.20	0.09
C.3.22	0	0	0	0	0.01	0	0	0	0	0.04
C.3.23	0	0	0	0	0	0	0	0	0.45	0
C.3.24	0	0.02	0	0	0.01	0	0	0	0	0
C.3.25	0	0	0	0	0	0	0.03	0	0	0
C.3.26	0	0.13	0	0.01	0	0.01	0	0.01	0	0
C.3.27	0.01	0	0	0	0.02	0	0	0.01	0	0
C.3.28	0.15	0	0.01	0	0.19	0	0	0.01	0	0.01
C.3.29	0.12	0	0	0	0.06	0	0.19	0.01	0.09	0.01
C.3.30	0.01	0	0	0.01	0	0	0.01	0.01	0	0.02
C.3.31	0.03	0	0	0	0.03	0	0.09	0.02	0	0.01
C.3.32	0	0	0	0.01	0	0	0	0	0	0
C.3.33	0	0	0	0	0	0	0	0	0	0.03
C.3.34	0	0	0	0	0	0	0	0	0	0
C.3.35	0.03	0.05	0.08	0	0.04	0.22	0.01	0.40	0.01	0.07
C.3.36	0.02	0.07	0.02	0.10	0	0.02	0.01	0	0.07	0.09
C.3.37	0.19	0	0.04	0.49	0.01	0.08	0.04	0.06	0.01	0.32
C.3.38	0.03	0.12	0.01	0.01	0.05	0.03	0	0.01	0	0
C.3.39	0	0	0	0	0.01	0	0	0.01	0	0
C.3.40	0	0.07	0.01	0	0.01	0	0.29	0	0	0
C.3.41	0.01	0	0	0	0	0	0	0	0	0
C.3.42	0	0.01	0	0	0	0.01	0	0	0	0.02
C.3.43	0.02	0	0.13	0	0.03	0.01	0.14	0.02	0	0
C.3.44	0	0.05	0	0	0	0	0	0	0	0.01
C.3.45	0	0.06	0.01	0	0.01	0	0.01	0	0	0

Table 12
Display Result Satellite Pictures from (C.3) into Classes from (B.1)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.3.1	0.16	0	0.28	0	0.38	0.04	0	0.09	0.01	0.04
C.3.2	0.06	0.02	0.04	0.01	0.31	0.09	0.01	0.29	0	0.15
C.3.3	0.06	0.13	0.03	0	0.16	0.06	0	0.12	0.01	0.44
C.3.4	0.16	0.08	0.05	0	0.30	0.04	0	0.08	0	0.29
C.3.5	0.10	0	0.09	0	0.20	0.04	0.02	0.28	0.02	0.25
C.3.6	0.14	0	0.01	0	0.05	0.22	0	0.09	0	0.49
C.3.7	0	0.25	0.06	0.20	0.41	0.04	0	0.02	0.01	0.01
C.3.8	0.26	0.02	0.04	0	0.64	0.01	0	0	0	0.04
C.3.9	0.03	0.19	0.02	0	0.16	0.12	0	0.05	0.01	0.42
C.3.10	0.04	0.01	0.37	0	0.44	0.04	0	0.06	0.01	0.04
C.3.11	0.23	0.06	0.02	0	0.60	0.04	0.01	0	0.01	0.02
C.3.12	0.13	0.24	0.03	0	0.53	0.01	0.02	0	0	0.02
C.3.13	0	0.05	0.29	0.41	0.08	0.02	0	0.12	0	0.02
C.3.14	0	0.83	0.10	0.01	0	0.02	0	0.01	0	0.02
C.3.15	0.04	0.04	0.06	0	0.11	0.02	0	0.44	0	0.29
C.3.16	0.06	0.43	0.06	0	0.11	0.07	0.01	0.06	0	0.20
C.3.17	0.21	0.10	0.04	0	0.30	0.03	0.01	0.09	0	0.23

C.3.18	0.40	0.02	0.10	0	0.29	0.02	0.14	0	0	0.02
C.3.19	0.06	0.01	0.11	0	0.79	0	0.02	0.01	0	0.01
C.3.20	0.15	0.04	0.02	0	0.57	0.01	0	0.09	0	0.12
C.3.21	0.02	0.02	0.30	0	0.02	0.37	0	0.02	0.01	0.25
C.3.22	0.01	0.22	0.09	0	0.19	0.06	0	0.02	0	0.41
C.3.23	0	0.13	0.33	0.13	0	0.09	0	0.03	0.25	0.05
C.3.24	0.17	0.20	0.02	0	0.49	0.02	0.01	0.01	0	0.09
C.3.25	0.16	0.04	0.07	0	0.65	0	0.01	0.02	0	0.04
C.3.26	0	0.42	0.17	0.09	0.03	0.08	0	0.09	0	0.12
C.3.27	0.13	0.02	0.01	0	0.23	0.01	0	0.43	0	0.17
C.3.28	0.19	0.06	0.05	0	0.62	0.02	0.01	0.01	0	0.05
C.3.29	0.17	0.07	0.07	0.01	0.58	0.01	0.02	0.03	0	0.04
C.3.30	0.07	0.07	0.06	0.01	0.11	0.01	0.01	0.43	0	0.23
C.3.31	0.08	0.04	0.07	0.01	0.42	0.02	0.04	0.22	0	0.09
C.3.32	0.04	0.18	0.05	0.04	0.08	0.15	0.02	0.15	0.02	0.27
C.3.33	0.01	0.23	0.03	0.01	0.04	0.13	0.02	0.11	0.01	0.41
C.3.34	0.17	0.04	0.08	0	0.46	0.01	0.01	0.13	0	0.11
C.3.35	0.04	0	0.17	0.01	0.15	0.03	0	0.44	0.01	0.14
C.3.36	0.13	0.10	0.16	0	0.44	0.13	0.01	0	0	0.02
C.3.37	0.06	0.02	0.22	0	0.19	0.07	0.01	0.03	0	0.40
C.3.38	0.15	0.01	0.02	0	0.80	0.01	0	0	0	0.01
C.3.39	0.07	0.13	0.30	0	0.18	0.17	0	0.07	0	0.09
C.3.40	0.03	0.01	0.03	0	0.58	0.03	0.01	0.01	0	0.02
C.3.41	0.25	0.14	0.01	0	0.34	0.01	0	0.05	0	0.19
C.3.42	0.03	0.27	0.03	0.13	0.03	0.09	0.02	0.16	0.01	0.23
C.3.43	0.14	0.05	0.08	0.01	0.60	0.01	0.08	0.02	0	0.02
C.3.44	0	0.65	0.07	0.02	0.01	0.07	0	0.07	0	0.10
C.3.45	0.04	0.01	0.25	0	0.67	0	0.01	0.01	0	0.01

Table 13
The Result of Mapping Aerial Photographs from (B.1) into Classes from (S.4)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.4.1	0.28	0.13	0.04	0.95	0	0.52	0.38	0.21	0.76	0.33
C.4.2	0	0	0.01	0	0.01	0	0	0	0	0
C.4.3	0	0.06	0.05	0	0.03	0.02	0	0.05	0	0.02
C.4.4	0.06	0.01	0.49	0	0.02	0.33	0	0.24	0.04	0.37
C.4.5	0.12	0	0.02	0	0.08	0	0	0	0	0
C.4.6	0	0.01	0	0.01	0	0	0	0.01	0	0
C.4.7	0.01	0.10	0	0	0.03	0	0	0	0	0
C.4.8	0	0.31	0	0.04	0.01	0.01	0.47	0.02	0	0.01
C.4.9	0.22	0	0.01	0	0.21	0	0	0.12	0	0.01
C.4.10	0	0.21	0.05	0	0.01	0.05	0	0.12	0.19	0.03
C.4.11	0	0.01	0	0	0.01	0	0	0	0	0
C.4.12	0.01	0.08	0	0	0.02	0	0.01	0.02	0	0
C.4.13	0.02	0	0	0	0.18	0	0	0.03	0	0
C.4.14	0.01	0	0	0	0.02	0	0	0	0	0
C.4.15	0.08	0	0	0	0.02	0	0	0	0	0
C.4.16	0	0	0	0	0.04	0	0	0	0	0
C.4.17	0.01	0.01	0.01	0	0.02	0.02	0	0.03	0	0.19
C.4.18	0.03	0	0.01	0	0.01	0	0	0.07	0	0
C.4.19	0.01	0.06	0.01	0	0.04	0.01	0	0.01	0.01	0
C.4.20	0.12	0	0.24	0	0.14	0.02	0.13	0.02	0	0
C.4.21	0.03	0.02	0.07	0	0.10	0.01	0	0.03	0	0.03

Table 14

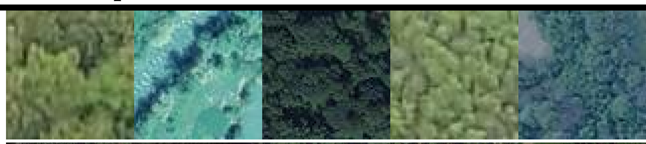
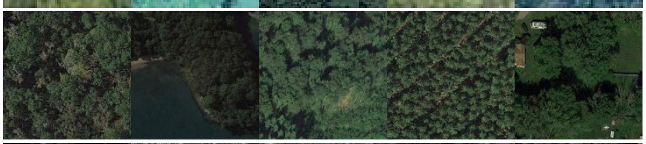
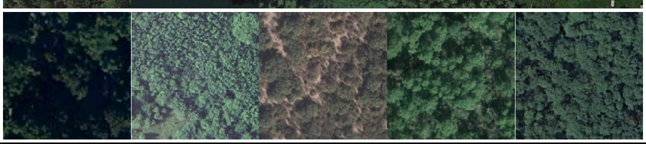
The Result of Mapping Satellite Images from (S.4) into Classes from (B.1)

	B.1.1	B.1.2	B.1.3	B.1.4	B.1.5	B.1.6	B.1.7	B.1.8	B.1.9	B.1.10
C.4.1	0	0.01	0.03	0.52	0	0	0	0	0.44	0
C.4.2	0.10	0	0.38	0	0.48	0.03	0	0	0	0.01
C.4.3	0.10	0.01	0.08	0	0.38	0.06	0	0.17	0.05	0.15
C.4.4	0.04	0	0.08	0	0.12	0	0	0.30	0.14	0.32
C.4.5	0.19	0	0	0	0.81	0	0	0	0	0
C.4.6	0	0.10	0.07	0.74	0.02	0	0	0	0.07	0
C.4.7	0.01	0	0	0	0	0.99	0	0	0	0
C.4.8	0	0.99	0	0.01	0	0	0	0	0	0
C.4.9	0.18	0	0.02	0.01	0.28	0	0	0.38	0	0.13
C.4.10	0.03	0.06	0.19	0	0.28	0.03	0	0.18	0.16	0.07
C.4.11	0.07	0	0.25	0	0.45	0	0.12	0	0	0.11
C.4.12	0.04	0	0	0	0.78	0.01	0	0.13	0	0.04
C.4.13	0	0	0	0	1.00	0	0	0	0	0
C.4.14	0	0	0.06	0	0.94	0	0	0	0	0
C.4.15	0.18	0	0.01	0	0.54	0	0	0.19	0	0.08
C.4.16	0.02	0	0.02	0	0.95	0	0.01	0	0	0
C.4.17	0	0	0	0	0	0	0	0	0	1.00
C.4.18	0.03	0	0.08	0.03	0.21	0	0	0.36	0	0.29
C.4.19	0	0.03	0.10	0	0.72	0.02	0	0.08	0	0.05
C.4.20	0.04	0	0.26	0	0.67	0	0	0.02	0	0.01
C.4.21	0.27	0.03	0.03	0	0.61	0	0	0	0	0.06

From the given data can be drawn the following conclusions. First of all, the classes reflecting natural formations (forests, fields of various kinds, reservoirs and rivers) have great compatibility from the point of view of displaying satellite images in UAVs - analogues. For example, classes C.4.8 and C.3.14 appeared in B.1.2 almost in full and all of them are annotated as forests. Classes C.4.17 (rivers) and C.2.16 (ponds) are also strongly reflected in class B.1.10 (bodies in general). Indeed, it might seem obvious, but it is worth noting that when reflected in reverse, such ambiguity disappears. For example, the same class of reservoirs B.1.10 when displayed in satellite classes relatively is equally distributed between C.4.1 and C.4.4 or with an ambiguous advantage (0.32) is reflected in the class of ships C.3.17. This shows that, from the point of view of natural formations, it is the data obtained with the help of satellite imaging that can serve to expand the UAV dataset.

Table 15

Examples of digital images of classes "Forest"

Class label	An example of a central office
B.1.2	
P.3.14	
P.4.8	

The most effective class from the point of view of mapping satellite images into UAV classes was class B.1.5 – non-industrial buildings. Classes C.4.5, C.4.13, C.4.14, C.2.9, by more than 80 percent, were reflected precisely in class B.1.5, while they themselves represent different types of buildings, which indicates that they you can supplement this class. On the other hand, the dataset as a whole can be supplemented with classes that have a not so high level of reflection in B.1.5 (from 0.3 to 0.75), but at the same time it is the largest. Examples of such are P.4.21, P.4.20, P.4.15, P.4.12, P.4.11, P.3.43, P.3.43, P.3.36, P.3.34. and other. Also, classes C.4.16, C.2.14 (parking lots) showed a rather high, but at the same time, false level of display - such indicators can also be considered a marker for selecting a new dataset class or expanding an already existing one (for example, motor vehicle class B.1.3).

Table 16
Examples of Images of Classes Related to Water Bodies

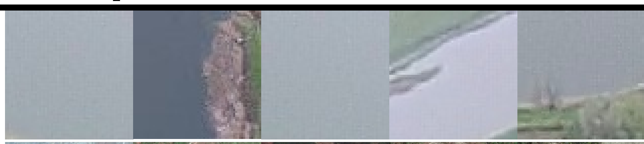
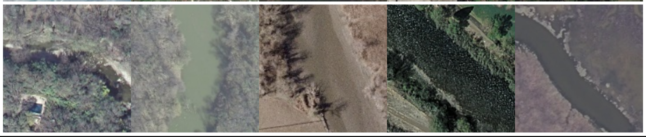
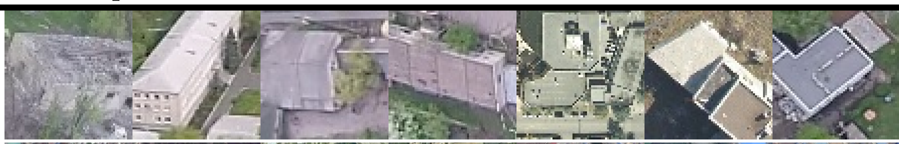
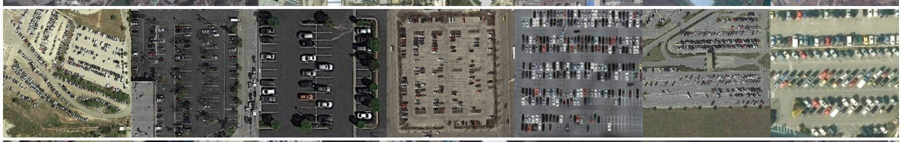
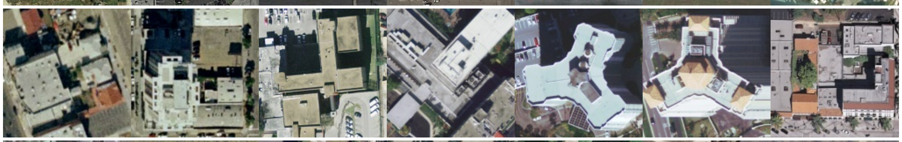
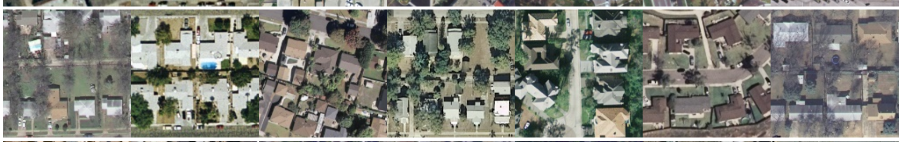
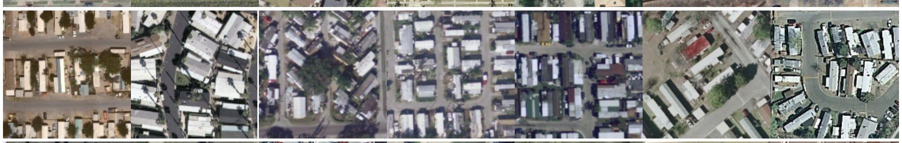
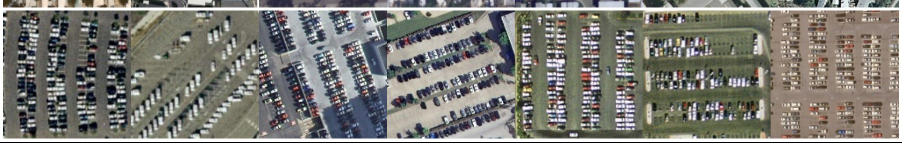
Class label	An example of a central office
B.1.10	
P.2.16	
P.4.17	

Table 17
Examples of images of building classes and strongly reflected in it

Class label	An example of a central office
B.1.5	
P.2.9	
P.2.14	
P.4.5	
P.4.13	
P.4.14	
P.4.16	

In addition, the division of the UAV construction class – the dataset into classes B.1.1, B.1.5, B.1.7 – showed its impracticality, because in B.1.1 and B.1.7 a significant share of satellite data was not displayed, and these classes themselves were displayed in meaningless, such as C.4.1, C.4.8 (fields and forests), C.3.1 (aircraft), C.2.4 (beaches).

3. Conclusions

In general, the study confirmed the feasibility of creating mixed-type datasets and the possibility of supplementing the UAV dataset with images of satellite data, or creating new classes based on them. In the perspective of future research, it is possible to highlight the creation of a universal "framework" set that could be easily modified to meet the needs of various tasks.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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